Bayesian approaches to Neural dynamics and coding

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All of our decisions are subject to uncertainty.

Estimate of how far you can jump

Uncertainty matters!
Analysing sensory scenes

Causal Model

Visual input

Neural network
Object present/not
Receptor spike/not

\[
\begin{align*}
&x_t^{\text{on}}, r_{\text{on}}, r_{\text{off}} \\
&s_t^{\text{on}}, s_t^{\text{off}}
\end{align*}
\]
\[ L_t = \log \left( \frac{p(x_t^1 = 1 \mid s)}{p(x_t^1 = 0 \mid s)} \right) \]

\[ w_i = \log \left( \frac{q_o + q_i}{q_o} \right) \]

\[ \frac{\partial L}{\partial t} = r_{on} \left( 1 + e^{-L} \right) - r_{off} \left( 1 + e^L \right) + \sum_i w_i s_t^i - \theta \]

Leak

Synaptic input
An analogy with a leaky integrate and fire neuron

\[ V_t = L_t - G_t \]
Time constant of integration depends on contrast.

\[ x_t \]

\[ O_t \]

Bair and Movshon 2004

Model

Contrast 1
Contrast 0.2
Contrast 0.05

Time

Contrast 1
Contrast 0.2
Contrast 0.05
Comparison with Linear Integrate and Fire

Bayesian

\[ V_t = L_t - G_t \]

Linear Integrate and fire

\[ \tau \dot{V} = -V + \sum_i w_i s_t^i \]
Information transmission about the stimulus
Towards a biophysical basis of spike-based inference

\[ \tau \dot{V} = \Phi(V) - V - r_{off} u V + \sum_{i} w_i S^i_t \]

Object almost certainly absent

Uncertain

Object almost certainly present

Adaptive currents

\[ \Phi(V) = e^{-V} - 1 \]

Spike based adaptation

\[ \dot{u} = (r_{off} - r_{on}) u - r_{off} u^2 + u O_t \]
Approx Bayesian ($I_h$+spike based adapt):

\[
\tau \dot{V} = \Phi(V) - V - r_{off} u V + \sum_{i} w_i s^i_t
\]

\[
\dot{u} = (r_{off} - r_{on}) u - r_{off} u^2 + u O_t
\]

Knock-out (IF):

\[
\tau \dot{V} = -V + \sum_{i} w_i s^i_t
\]
Inference in single spiking neurons

$\begin{align*}
\text{Wait for transition} \\
\text{Integrate} \\
\text{Wait for transition.}
\end{align*}$

Firing threshold

$\begin{align*}
\mathbf{r}_{\text{on}} I_{\text{adapt}} \\
\log \left( \frac{r_{\text{on}}}{r_{\text{off}}} \right) \\
\mathbf{r}_{\text{off}} I_h
\end{align*}$
Conclusion 1: Bayesian spiking neuron

- Integrate and fire neurons can be interpreted as Bayesian integrators.
- Biophysical parameters have functional interpretations.
- Spikes represent increases in probability.
- Optimal neural dynamics can be learnt in an unsupervised way (on-line Expectation maximization).
Analysing sensory scenes

Visual input

Causal Model

Neural network
Receptive fields

RF for V1 simple cell:

Hubel and Wiesel, 1962
Receptive fields

RF for V1 simple cell:

Hubel and Wiesel, 1962
Responses to natural scene are poorly predicted by the RF.

Machens CK, Wehr MS, Zador AM. J Neurosci. 2004
Multiple excitatory and suppressive components

Schwartz et al 2006
Receptive fields depend on surround stimuli

[Sillito et al, Nature 1995]

Angelucci et al 2001
Sparzening and decorrelation by the contextual surround

Vinje and Gallant, Science 2000
Analysing sensory scenes

Causal Model

Visual input

Neural network
Receptive and Predictive fields

« edge predictor »

« edge detector »
Predictive fields

« edge predictor »
Predictive fields

« edge predictor »
Predictive fields

« edge predictor »
Predictive fields

« edge predictor »
Causal inference to solve ambiguities

\[ x_t^1 \quad \text{OR} \quad x_t^2 \]

\[ S_t \]

\[ L_t^1 \quad L_t^2 \]
Input targeted divisive inhibition

Input targeted inhibition performs
Explaining away
Prediction by the context

\[
\frac{\partial L_j}{\partial t} = \varphi'(L_j) + \sum_i w_{ij}^t s_t^i
\]

\[
w_1^t = \log \left( \frac{q_o + q_1 + p(x_t^2 = 1 | s)q_2}{q_o + p(x_t^2 = 1 | s)q_2} \right)
\]

Input targeted divisive inhibition
Input targeted divisive inhibition (ITI)

\[ \frac{\partial L_j}{\partial t} = \varphi'(L_j) + \sum_i \frac{w_{ij}}{1 + \sum_{k \neq j} w_{ik} p_k(t)} s_i^t - \theta \]

Contextual prediction

\[ p_k(t) = \frac{e^{L_k}}{1 + e^{L_k}} \]
Importance of ITI for object detection

Without ITI

ITI
Implication for sensory receptive fields

Causal fields learnt from natural movies

“Blobs”

Model causal fields
Response to natural scenes
Decorrelation of natural scenes
Selectivity relies on context from the entire scene.
Coarse-to-fine changes in RF over time

With divisive inhibition  
Without divisive inhibition

Ringach and Malone, 2006
Woergoetter et al 1998
Coarse to fine changes as a function of input reliability

Sceniak et al 1998 (V1)

Sceniak et al 2001 (V1)

Salomon et al 2006 (M-type RGC)
Coarse to fine changes as a function of input reliability

High contrast, long integration

Low contrast, short integration

Discrimination

Detection
The surround reshapes the receptive field
Effect of spatial surround: Saliency

[Sillito et al, Nature 1995]
Non-separable center and surround
Effect of temporal surround: Adaptation

Adaptation

rate

stimulus position

amplitude change

preferred position
Effect of temporal surround: Perceptual bias away from adapted position
Effect of temporal surround: Perceptual bias away from adapted position
Effect of temporal surround: Perceptual bias away from adapted position

Adaptation

Proba

Real

psth

10
20
30

100 200 300 400 500

St
Sensory neurons do not represent local contrast or salience or novelty
Predictive fields are invariant

Receptive fields are defined by the context
Dynamic reshaping of receptive fields

![Diagram showing dynamic reshaping of receptive fields with time and effective input graphs.](image-url)
With high degrees of overlap, receptive fields are meaningless.
How can we measure predictive fields?

- Predictive fields
- Receptive fields

- Low Contrast, subthreshold, short stimuli rather than optimal, high contrast stimuli.

- Measuring subthreshold currents (Patch clamp)

- Selectivity of sustained responses.

- Fit multi-electrode recordings.
Using low contrast stimuli

Predictive fields  Receptive fields
Recursive method for measuring predictive fields

Predictive fields  Receptive fields
Multi-electrode recordings
Sustained responses as signature of true selectivity
Expectations redirect sensory flows

Prior for table
Conclusion 2: Normative approach to neurophysiology

- Neural networks are mirror images of underlying causal world models.
- Contextual effects on RFs are signature of perceptual inference.
- Competition (lateral inhibition) is input selective and divisive.
- Perceptual inference is a collective, dynamical process in sensory networks.
- Selectivity of visual cells should be characterized by weak, near threshold stimuli (faint, low contrast, short, noisy) rather than optimal stimuli.
- Future directions: feedback, learning, neural basis of psychiatric disorders.
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